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Research papers

Stricter nutrient criteria are required to mitigate the impact of climate change on harmful cyanobacterial blooms

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ABSTRACT

Climate change has the potential to exacerbate eutrophication and the risk of harmful algal blooms in lakes. Periodic adjustment of nutrient criteria, as the cornerstone of eutrophication control and water quality management, is expected to help mitigate the impact of climate change on harmful cyanobacterial blooms. The nutrient criteria that do not threaten the function of the water body determined with generalized additive models (GAMs) were 0.88 mg/L for total nitrogen (TN) and 0.021 mg/L for total phosphorus (TP) during the period of 1996–2005 based on 26 lakes and reservoirs in China. Climate change-induced temperature increases will substantially reduce the required nutrient criteria by 46.17% for TN and 15.24% for TP in lakes and reservoirs by the end of the century under the "business-as-usual" scenario. The results indicate that some lakes that currently meet the nutrient criteria could become dominated by cyanobacteria and experience blooms in a warmer future, even without increases in nutrient inputs. Therefore, as climate change persists, nutrient loads should be further reduced to achieve the desired water quality without the threat of eutrophication. Strict control of TP would be particularly advantageous to suppress algal blooms. It is imperative that water quality management strategies account for the impact of projected future climate changes on nutrient criteria and that nutrient criteria are periodically modified. The corresponding nutrient risk thresholds should be determined to ensure that lakes and reservoirs escape the threat of harmful algal blooms under the impact of extreme weather events.

1. Introduction

Eutrophication, caused by substantial increases in nutrient loads from agricultural run-off, industrial activity, and wastewater treatment facilities, is a growing global problem. Moreover, global warming is expected to increase the frequency, intensity, and duration of cyanobacterial blooms in many aquatic ecosystems worldwide (Couture et al., 2018; Huisman et al., 2018; Michalak, 2016; Xia et al., 2012). Climate change can both directly and indirectly affect the hydrology, aquatic environment, and ecosystem structure and function of lakes and reservoirs. For instance, surface runoff can be influenced by changes in precipitation, with subsequent impacts on nutrient loads from catchments, which is an important source of nutrients for phytoplankton (Couture et al., 2018; Xia et al., 2015). Moreover, increasing temperatures are expected to expand the thermal stratification period, deepen the thermocline, and promote earlier onset and proliferation of algal blooms, which could threaten aquatic ecosystems (Deng et al., 2014; Zhang et al., 2016a; Zhang et al., 2014).

Nutrient reduction strategies aimed at alleviating eutrophication may be weakened by the impacts of climate change on the aquatic environment (Havens and Paerl, 2015), given that climate change is expected to severely affect the ability to control blooms, and in some cases could make it near impossible. For example, total phosphorus (TP) and total nitrogen (TN) concentrations in Lake Taihu, the third-largest freshwater lake in China, decreased by 42.5% and 31.2% from 2007 to 2015, respectively, but the frequency and intensity of cyanobacterial blooms did not significantly decrease due to climate-driven changes (Yang et al., 2016). Thus, the nutrient load especially internal load must be further reduced while the temperature is increased (Chen et al., 2018).

Nutrient criteria represent the maximum acceptable concentrations of nutrients that do not threaten the function of the waterbody, which is

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crucial for cultural eutrophication control and lake and reservoir water quality protection (Huo et al., 2018; Kelly et al., 2015). Research has shown that climate change factors, such as temperature, precipitation, and wind speed, influence the relationships between nutrients and chlorophyll *a* (Chl *a*), and impact the development of nutrient criteria (Liu et al., 2018). However, little research has assessed the need for changes in nutrient criteria as climate change persists or the impact of climate change on nutrient criteria.

To address this gap in knowledge, we quantified the contribution of climatic factors, in particular air temperature, to Chl *a* concentrations and estimated the impact of future climate scenarios on nutrient criteria using generalized additive models (GAMs) (Alcaraz et al., 2011; Grieve et al., 2017). The estimates were derived from anticipated changes in air temperature as projected under three Climate Model Intercomparison Project Phase 5 (CMIP5) models for four climate scenarios, such as the RCP2.6 mitigation scenario, the RCP4.5 and RCP6.0 stabilization scenarios, and the RCP8.5 business-as-usual scenario, for eight future time periods, which are in ten-year increments from 2016 to 2095. As a climate-sensitive area, the largest increases in temperature will most likely occur in China (IPCC, 2001); therefore, the impacts on 26 lakes and reservoirs were estimated within Mainland China. Although a number of factors could impact nutrient criteria, we focused specifically on the impacts of changes in temperature in the absence of other concurrent changes, such as light intensity and extremely weather events, because these impacts cannot be avoided through management efforts.

2. Materials and methods

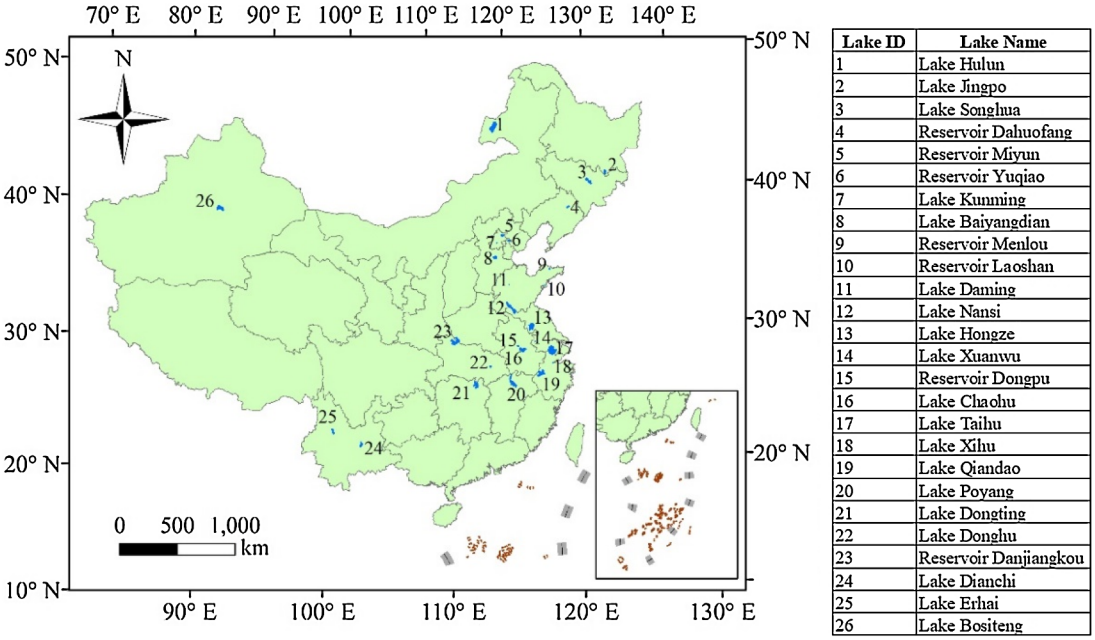
2.1. Study area

In this study, 17 lakes and 9 reservoirs in Mainland China were investigated to identify the impact of climate change on nutrient criteria (Fig. 1). Table S1 (Supporting Information, SI) presents information on the 26 studied lakes and reservoirs. The analysis of the TN/TP ratios indicated that all studied lakes and reservoirs were primarily phosphorus-limited, and that the growth of algal was more sensitive to changes in phosphorus than nitrogen (Schindler et al., 2008; Wu et al., 2017).

2.2. Data collection

Water quality data for the 26 lakes and reservoirs were obtained from the China National Environmental Monitoring Centre. TN, TP, and Chl *a* concentrations were determined at several sites in each lake and reservoir during monthly routine monitoring from 2006 to 2010. The TN, TP, and Chl *a* concentrations were analyzed in a laboratory using the standard testing procedures recommended by the Ministry of Environmental Protection of China (PRC MEP, 2002), these procedures are summarized here. TN was determined using a spectrophotometric procedure after the alkaline persulfate digestion of the sample. TP was measured using a spectrophotometric procedure after the acid potassium persulfate digestion of the sample. The detection limits for TP and TN were 0.01 mg/L and 0.1 mg/L, respectively. For Chl *a* analysis, a certain number of samples were filtered and blocked algae by filter membrane, grinded and broken algae cells, and chlorophyll was extracted by acetone solution. After centrifugation separation, the absorbance of the extract was determined at 750, 664, 647 and 630 nm wavelengths, respectively. The concentration of chlorophyll in water was calculated according to the formula. To maintain the validity of the data, observations below the limits of detection were replaced with one-half the detection limit for the given variable, as the processed data were sufficiently accurate to determine descriptive statistics (EPA, 2006; Huo et al., 2013). The monthly averages of the variables in each lake or reservoir were calculated as the model input dataset in this study.

Meteorological data simulated by three global climate models (GCMs) of the CMIP5 under four greenhouse gas emission scenarios were downloaded from the World Climate Research Programme. The three GCMs, GISS-E3-H, HadGEM2-ES, and MRI-CGCM3 (Table 1), were expected to perform well for the simulation of surface air temperature in China (Hu et al., 2014; Yan et al., 2013). The ensemble mean values of these three GCMs were calculated using equal weights, which could model the spatial and temporal variation characteristics of meteorological data better than a single GCM at a regional scale (Zhang et al., 2016b). The observation dataset CN05.1 obtained from the China Meteorological Administration was used to evaluate the performance of the GCMs in simulating surface air temperature climatology in China (Wu and Gao, 2013; Xu et al., 2009). Monthly average surface air temperature (tas; ˚C) was selected as the climatic factor based on



Lake ID	Lake Name
1	Lake Hulun
2	Lake Jingpo
3	Lake Songhua
4	Reservoir Dahuofang
5	Reservoir Miyun
6	Reservoir Yuqiao
7	Lake Kunming
8	Lake Baiyangdian
9	Reservoir Menlou
10	Reservoir Laoshan
11	Lake Daming
12	Lake Nansi
13	Lake Hongze
14	Lake Xuanwu
15	Reservoir Dongpu
16	Lake Chaohu
17	Lake Taihu
18	Lake Xihu
19	Lake Qiandao
20	Lake Poyang
21	Lake Dongting
22	Lake Donghu
23	Reservoir Danjiangkou
24	Lake Dianchi
25	Lake Erhai
26	Lake Bositeng

Fig. 1. Names and locations of the 26 studied lakes and reservoirs in China.

Table 1
General information on the chosen global climate models.

ID	Model name	Ensemble	Institution	Country	Horizontal resolution (lon. × lat.)
1	GISS-E2-H	R1I1P1	NASA Goddard Institute for Space Studies	United States	2.5 × 2.0
2	HadGEM2-ES	R1I1P1	Met Office Hadley Centre	United Kingdom	1.875 × 1.25
3	MRI-CGCM3	R1I1P1	Meteorological Research Institute	Japan	1.125 × 1.125

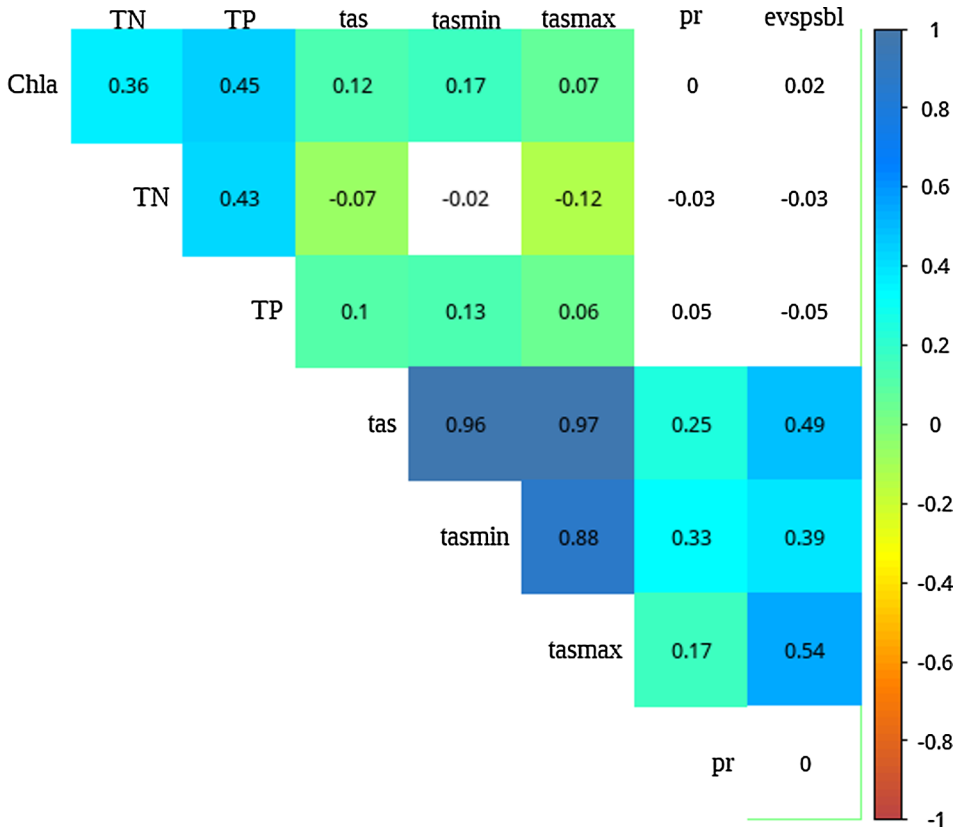


Fig. 2. Spearman correlation coefficients of the variables in the 26 studied lakes and reservoirs.

Table 2
Overview of the selected representative concentration pathways (RCPs).

Scenario name	Description
RCP 2.6	The radiative forcing goes to a peak at 3 W/m^2 before 2100 and then declines to 2.6 W/m^2 by 2100, and the CO_2 equivalent concentration peaks at 490 ppm before 2100 and then declines.
RCP 4.5	The radiation forcing is stable at 4.5 W/m^2 without overshoot after 2100, and the CO_2 equivalent concentration stabilizes at 650 ppm.
RCP 6.0	The radiation forcing is stable at 6 W/m^2 without overshoot after 2100, and the CO_2 equivalent concentration stabilizes at 850 ppm.
RCP 8.5	The radiation forcing goes up to 8.5 W/m^2 in 2100, while the CO_2 equivalent concentration goes up to 1370 ppm.

Spearman correlation analysis (Fig. 2) and variance inflation factors (see Text S1 in SI). Four greenhouse gas emission scenarios (Table 2), RCP2.6 (mitigation scenario), RCP4.5 and RCP6.0 (stabilization scenarios), and RCP8.5 (business-as-usual scenario with no climate policy), were used to predict the future nutrient criteria (Moss et al., 2010).

2.3. Statistical methods

The relationships among Chl *a*, nutrient variables, and meteorological variables were analyzed with Spearman correlation analyses performed using SPSS ver. 20.0 (IBM Corp., Armonk, NY, USA) and R 3.4.4 (R Core development team) (see SI). Meteorological data were processed using ArcGIS ver. 10.2 (ESRI, Redlands, CA, USA) and MATLAB 2017b (MathWorks, Natick, MA, USA). Taylor diagram was plotted in MATLAB 2017b to provide a concise statistical summary of how well the three individual GCMs and three-model ensemble matched the observation data in terms of their correlation, root-mean-square difference, and standard variances (Taylor, 2001).

The GAMs (G1, G2, and G3) were performed with R ver. 3.4.4 software using the "gmcv" package to combine nutrient concentrations and tas as the explanatory variables and Chl *a* as the response variable. GAMs are nonparametric regression models, meaning that the relationships between the stressor and response variables are established by the data rather than an *a priori* statistical distribution (Alcaraz et al., 2011; Grieve et al., 2017). The smooth terms of the stressor variables were simulated by thin plate regression spline, and the parameters of the smooth function were selected via synthesis considering the generalized cross-validation (GCV) criterion and the Akaike's information criterion (AIC) to ensure that the models could explain most information of variables while avoiding over-fitting (Song et al., 2015; Wood,

2017). The smooth function, representing the relative importance of each stressor variable to the response variables (Paerl et al., 2016), was used to calculate the contribution of the stressor variable to the variation in the response variable.

The numeric nutrient criteria were derived from these models using fixed response variable values (EPA, 2010; Huo et al., 2014b), and the standard error was used to calculate the prediction interval of the numeric criteria (Fahrmeir and Lang, 2001; Marra and Wood, 2012). To prevent under- and over-protection, 5 μg/L Chl *a* was considered as a reasonable limit to ensure the safety of lakes and reservoirs (Huo et al., 2014a). Nutrient criteria should be set so as to protect lakes and reservoirs during the warmest period of the year. Therefore, the air temperature in July was selected as the fixed climatic factor to derive the nutrient criteria, which represents the highest monthly air temperature for the studied lakes and reservoirs. According to the IPCC, variations in climate can lead to differences in the impacts at an interdecadal scale (Bindoff et al., 2013); the future interdecadal fluctuation of temperature under different scenarios was calculated starting in 2006 to predict the numeric nutrient criteria.

3. Results and discussion

3.1. Temporal variations in nutrient criteria under future climate change

Based on the TN/TP ratios, the studied lakes and reservoirs were primarily phosphorus-limited, indicating that phosphorus is the primary restrictive nutrient for algal growth. However, previous studies have shown that nitrogen is equally likely to limit algal growth in inland waters (Lewis et al., 2011). Based on these considerations, three GAMs were developed using Chl *a* as the response variable, and TN, TP, and tas as the explanatory variables for the period of 2006–2010 (Table 3). All parameters in all three models were significant ($p < 0.001$), and the AIC and GCV results indicated that these explanatory variables were suitable for the models. Contributions of temperature, TN, and TP to Chl *a* based on GAMs were described in Text S2 (see in SI).

G1 and G2 were developed by considering only single-nutrient stressor variables and one climatic factor. The nutrient criteria from 1996 to 2005 simulated by the GAMs were 0.88 TN mg/L and 0.021 TP mg/L, which were considered as the historical nutrient criteria. The anticipated changes in future temperature patterns under the business-as-usual scenario could lead to large and robust decreases in the TN and TP criteria by the end of the century (Fig. 3). Without considering the impact of TP, the TN criterion was 5.71%, 13.69%, and 21.71% lower by the end of this century under the RCP2.6, RCP4.5, and RCP6.0 scenarios, respectively, than the historical criterion. By contrast, there was a sharp decrease in the TN criterion under the RCP8.5 scenario to 0.47 mg/L by the end of this century, 46.17% lower than the historical criterion. The predicted TP criterion exhibited a similar trend, and the predicted TP criterion decreased by 3.81%, 7.62%, 9.52%, and 15.24% of the historical criterion by the end of the century under the four scenarios, respectively. Overall, the TP criterion exhibited a smaller range in variation than the TN criterion.

G3 model was developed by considering both nitrogen and phosphorus as stressor variables and temperature as the climatic factor to simulate the impact of the covariation of TN and TP on Chl *a* (Table 3). The nitrogen or phosphorus criteria were estimated by fixing the other nutrient variable using the results of G1 and G2 at a given time. The nutrient criteria of 1996–2005 simulated by G3 were considered as the historical criteria.

Table 3
Summary of the models developed using a GAM approach.

Model ID	Model formula*	R^2 (adj.)	p-value	AIC	GCV
G1	lg(Chl *a*) ~ s(TN) + s(Tas)	0.192	< 0.001	13.78	0.281
G2	lg(Chl *a*) ~ s(TP) + s(Tas)	0.234	< 0.001	10.78	0.266
G3	lg(Chl *a*) ~ s(TN) + s(TP) + s(Tas)	0.295	< 0.001	20.26	0.246

* S(x): smooth function of indicator x; Chl *a*: chlorophyll *a* (μg/L); TN: total nitrogen (mg/L); TP: total phosphorus (mg/L); tas: monthly average surface air temperature (°C); length of the dataset n = 1362.

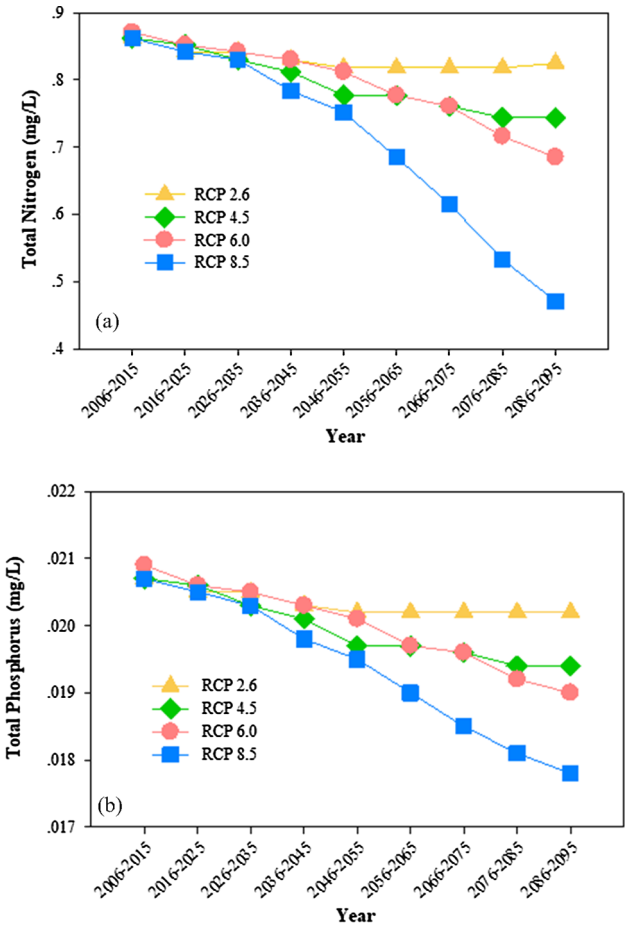


Fig. 3. Predicted numeric criteria of (a) TN and (b) TP under four change climate scenarios.

By fixing the TP criterion using the results of G2, the historical TN criterion simulated by G3 was 1.89 mg/L, which was much higher than that of G1. Although declining trends in the predicted TN criterion were observed under the different scenarios, no sharp decline was observed (Fig. 4a). The minimum predicted TN criterion of 1.80 mg/L was observed at the end of the century under RCP8.5, which was only 4.82% lower than the historical criterion. The historical TP criterion simulated by G3 was 0.034 mg/L, which was higher than that of G2. G3 yielded similar trends in the TP criterion as G2 (Fig. 4b). In particular, the TP criterion under RCP2.6, RCP4.5, RCP6.0, and RCP8.5 was 4.65%, 12.21%, 17.73%, and 37.50% lower than the historical criterion by the end of the century, respectively. In the case of strict control of TN, the TP criterion still declined sharply under the influence of increasing air temperature.

These results indicated that, under strict control of TP loading, the TN criterion exhibited a very slow decreasing trend under global warming. This suggests that there would be little risk of algal overgrowth under strict TP loading control, even in water with high TN concentrations under future warmer climates. Therefore, strict control of TP would be more advantageous for suppressing cyanobacterial blooms than TN control in a future warmer climate. This may be because phosphorus is often the key limiting factor for phytoplankton growth, and controlling phosphorus loading is a primary goal for lake/

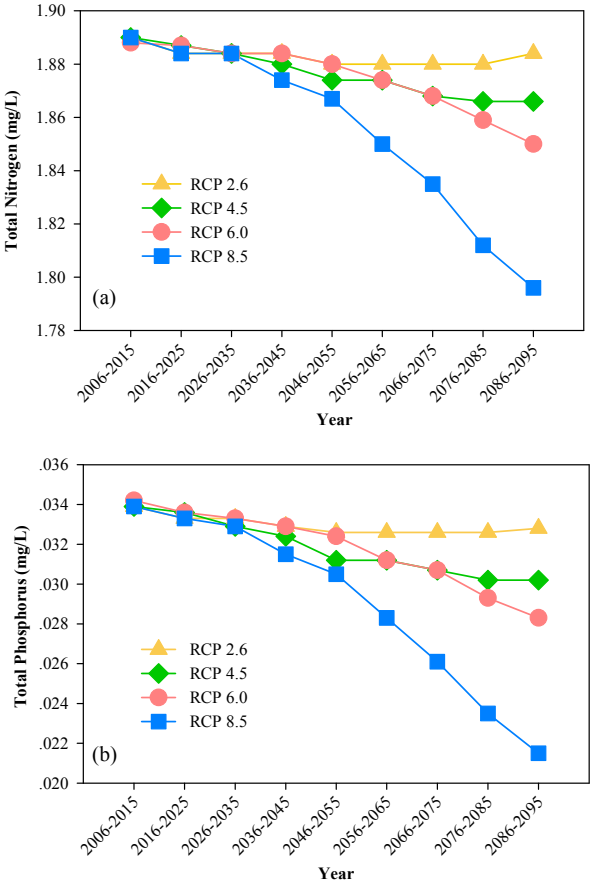


Fig. 4. Percentage declines in the (a) TN and (b) TP criteria inferred by the G3 model under four climate change scenarios.

reservoir management (Schindler et al., 2008). The predicted nutrient criteria of G3 were higher than those of G2, indicating that, under a dual nutrient management strategy, each nutrient could be controlled under less-strict criteria than under single-nutrient management strategies. Similarly, a recent study (Paerl et al., 2016) of integrated nutrient-loading analyses, nutrient-addition bioassays, and nutrient cycling recommended that a dual-nutrient-management strategy was much more reasonable than single-nutrient strategies.

3.2. Analysis of the impacts of climate change on nutrient criteria

The trends in nutrient criteria were in contrast to those of temperature (Fig. 5) in response to climate change, indicating that stricter nutrient criteria should be set with increasing air temperature. For instance, at a given nutrient concentration, increasing temperatures are expected to increase nutrient availability to cyanobacteria. Water temperature is highly correlated with primary productivity and affects cyanobacterial development (Wang et al., 2016). Moreover, higher temperatures promote the growth of *Microcystis*, which have been found to have optimal temperatures for growth and photosynthesis at or above 25 °C (Davis et al., 2009). Therefore, rising temperatures could offer a distinct growth advantage to *Microcystis* over eukaryotic primary producers under eutrophic conditions. In addition, higher temperatures could decrease the viscosity of surface water, increasing the sedimentation rate of eukaryotic phytoplankton and further strengthening the competitive advantage of *Microcystis*, because cyanobacteria can regulate their buoyancy to optimize nutrient and light acquisition (Paerl and Huisman, 2009).

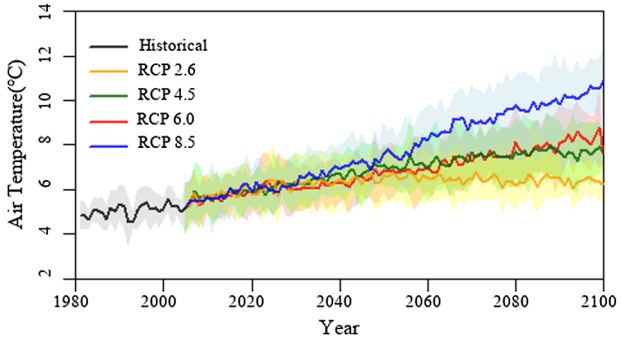


Fig. 5. Variations in the ensemble mean air temperature based on historical data and simulated with the GISS-E3-H, HadGEM2-ES, and MRI-CGCM3 models four climate change scenarios.

The results indicated that some lakes with nutrient levels below the criteria could develop cyanobacterial dominances and experience blooms under warmer climates, even without further rises in nutrient inputs. Moreover, the predicted TN criteria decreased much more rapidly than the TP criteria in response to warming, indicating that efforts to reduce TP inputs would generally be more effective than efforts to reduce TN inputs (Grizzetti et al., 2012).

3.3. Uncertainty analysis

Surface air temperature is an important climatic factor for lakes, since it can have direct or indirect influences the physicochemical variables of lakes (Dong et al., 2012; Wu et al., 2014). In this study, the ensemble simulated averages of three GCMs were applied to establish the GAMs and infer nutrient criteria under future warmer climates. Comparing the CN05.1 observation dataset with the GCM results with a Taylor diagram (Fig. 6), the selected GCMs appeared to exhibit good performance in simulating surface air temperature in China during 1996–2005. Moreover, the standard deviation ratios of the simulated GCM data to the CN05.1 observation data were between 1.03 and 1.22, and the correlation coefficients between the simulated and observation data were all above 0.9, indicating that the spatial distribution of the simulated GCM data was similar to that of the observation data (Taylor, 2001). Hence, the three-model ensemble values could accurately simulate the spatial and temporal variation characteristics of surface air temperature in China.

In the absence of human activities, other environment factors aside

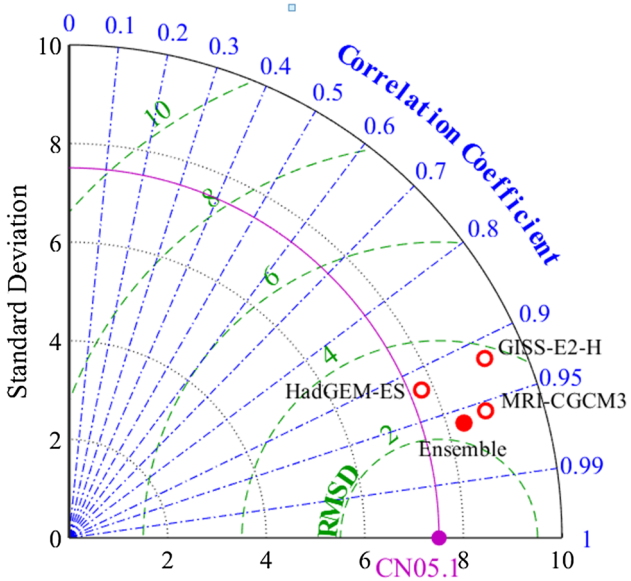


Fig. 6. Taylor diagrams of the simulated 20-year (1986–2005) monthly surface air temperature over China from three CMIP5 models.

from TP, TN, and temperature (e.g., light intensity, water color, and suspended sediment) can promote or inhibit algal growth (Huo et al., 2014a). Light intensity is an important condition for phytoplankton growth, which is related to the uptake of phosphorus and other micronutrients (Paerl et al., 2011). However, no significant changes on the growth rate of phytoplankton are observed at light intensities greater than 150–200 μE/m^2s (Tian et al., 2018). Hence, light intensity could be ignored in this study. Moreover, water color can change the light available for photosynthesis, and increased suspended sediments, which often coincides with increased N and P concentrations, also reduces light availability (US EPA, 2010). Therefore, these factors should be considered in future models.

Climate change has altered the assemblage structure of phytoplankton and production of microcystin (Davis et al., 2009; Sienkiewicz et al., 2017; Wood et al., 2016). In particular, climate-driven changes in water temperature can modify phytoplankton communities by favoring bloom-forming cyanobacteria, which can exploit warmer conditions (Havens and Paerl, 2015). Sienkiewicz et al. (2017) reported that climate warming drove changes in diatom species composition and almost all planktonic taxa abruptly decreased in frequency, which became dominated by benthic forms in Spitsbergen lake at the beginning of the 20th century. Therefore, changes in algal composition can cause major alterations in toxin concentrations and compositions during cyanobacterial blooms (Yu et al., 2014). Moreover, positive relationships ($p < 0.001$) have been identified between microcystin and water temperature, and the sensitivity of temperature is related to the nutrient levels in the water (Shi et al., 2017; Wood et al., 2016). For instance, Davis et al. (2009) showed that with continually enhancing surface water temperatures in laboratory experiments, toxic *Microcystis* exhibited more significant growth rates than non-toxic *Microcystis*, and could synthesize more microcystin synthetase, suggesting that climate warming may additively promote the growth of toxic, rather than non-toxic, populations of *Microcystis*, leading to blooms with higher microcystin contents (Davis et al., 2009). The impacts of climate change on the assemblage structure of phytoplankton and microcystin production should be carefully considered within the context of evolving eutrophication management strategies.

In addition, the release of internal nitrogen and phosphorus loads in lakes should be also attracted much attention, which hinder the improvement of water quality and sustain the eutrophication for decades, even if external P loading source has been effectively reduced. The rate of sediment P release will increases with the increase of temperature (Ding et al., 2018). Extreme weather events (EWEs) driven by climate change have a more important role in extended bloom formation after nutrient levels are reduced (Wang et al., 2016). EWEs, such as heavy rainfall events, extreme heat, and large storms, can increase nutrient loading, primary productivity, and sediment resuspension, promoting the formation of cyanobacterial blooms (Couture et al., 2018; Ouyang et al., 2017). Hence, corresponding nutrient risk thresholds must be determined to ensure that the water quality of lakes and reservoirs escapes the threat of eutrophication under the impact of EWEs. Moreover, the difference of hydraulic retention time between different lakes and reservoirs will also affect the change of nutrient nutrient with the increase of temperature. Further studies should consider the effect of hydraulic residence time on nutrient criteria.

4. Conclusion

The impact of climate change on nutrient criteria was estimated with GAMs using Chl *a* as the response variable, and TN, TP, and tas as the explanatory variables. The results indicated that future climate change could significantly impact nutrient criteria in lakes and reservoirs. At lower temperatures, less-stringent nutrient criteria could be applied due to the lower nutrient availability to cyanobacteria. By contrast, temperature increases could significantly enhance Chl *a* concentrations, suggesting that lakes with nutrient concentrations within the existing nutrient criteria could develop a dominance of cyanobacteria and experience blooms under warmer future scenarios, even without further increases in nutrient inputs. To ensure that cyanobacteria occurrence frequencies remain low, stricter nutrient criteria should be developed to achieve the desired water quality without the threat of eutrophication under a future warmer climate. In particular, the strict control of TP would be more advantageous to suppress cyanobacterial blooms than that of TN in the lakes and reservoirs studied. Moreover, nutrient risk thresholds should be determined to ensure that the water quality of lakes and reservoirs escapes from the threat of eutrophication under the impacts of EWEs. Overall, climate change should be considered in eutrophication mitigation strategies and should be taken into consideration in the determination of nutrient criteria.

Acknowledgments

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2018.12.030.

References

Alcaraz, C., Caiola, N., Ibanez, C., 2011. Bioaccumulation of pollutants in the zebra mussel from hazardous industrial waste and evaluation of spatial distribution using GAMs. Sci. Total Environ. 409 (5), 898–904.
Bindoff, N.L., Willebrand, J., Artale, V., Cazenave, A., Gregory, J., Gulev, S., et al., 2013. Climate Change 2013: The Physical. Science Basis, IPCC.
Chen, M.S., Cui, J.Z., Lin, J., Ding, S.M., Gong, M.D., Ren, M.Y., Tsang, D.C.W., 2018. Successful control of internal phosphorus loading after sediment dredging for 6 years: a field assessment using high-resolution sampling techniques. Sci. Total Environ. 616–617, 927–936.
Couture, R.M., Moe, S.J., Lin, Y., Kaste, O., Haande, S., Lyche Solheim, A., 2018. Simulating water quality and ecological status of Lake Vansjo, Norway, under land-use and climate change by linking process-oriented models with a Bayesian network. Sci. Total Environ. 621, 713–724.
Davis, T.W., Berry, D.L., Boyer, G.L., Gobler, C.J., 2009. The effects of temperature and nutrients on the growth and dynamics of toxic and non-toxic strains of Microcystis during cyanobacteria blooms. Harmful Algae 8 (5), 715–725.
Deng, J., Qin, B., Paerl, H.W., Zhang, Y., Ma, J., Chen, Y., 2014. Earlier and warmer springs increase cyanobacterial (Microcystis spp.) blooms in subtropical Lake Taihu, China. Freshw. Biol. 59 (5), 1076–1085.
Ding, S.M., Chen, M.S., Gong, M.D., Fan, X.F., Qin, B.Q., Xu, H., Gao, S.S., Jin, Z.F., Tsang, D.C.W., Zhang, C.S., 2018. Internal phosphorus loading from sediments causes seasonal nitrogen limitation for harmful algal blooms. Sci. Total Environ. 625, 872–884.
Dong, X., Bennion, H., Maberly, S.C., Sayer, C.D., Simpson, G.L., Battarbee, R.W., 2012. Nutrients exert a stronger control than climate on recent diatom communities in Esthwaite Water: evidence from monitoring and palaeolimnological records. Freshw. Biol. 57 (10), 2044–2056.
Fahrmeir, L., Lang, S., 2001. Bayesian inference for generalized additive mixed models based on Markov random field priors. J. R. Stat. Soc. Ser. C-Appl. Stat. 50, 201–220.
Grieve, B.D., Hare, J.A., Saba, V.S., 2017. Projecting the effects of climate change on Calanus finmarchicus distribution within the U.S Northeast Continental Shelf. Sci. Rep. 7 (1), 6264.
Grizzetti, B., Bouraoui, F., Aloe, A., 2012. Changes of nitrogen and phosphorus loads to European seas. Global Change Biol. 18 (2), 769–782.
Havens, K.E., Paerl, H.W., 2015. Climate Change at a Crossroad for Control of Harmful Algal Blooms. Environ. Sci. Technol. 49 (21), 12605–12606.
Hu, Q., Jiang, D., Fan, G., 2014. Evaluation of CMIP5 models over the qinghai-tibetan plateau. Chinese J. Atmos. Sci. 38 (5), 924–938.
Huisman, J., Codd, G.A., Paerl, H.W., Ibelings, B.W., Verspagen, J.M.H., Visser, P.M., 2018. Cyanobacterial blooms. Nat. Rev. Microbiol. 16 (8), 471–483.
Huo, S., Ma, C., Xi, B., Gao, R., Deng, X., Jiang, T., et al., 2014a. Lake ecoregions and nutrient criteria development in China. Ecol. Indic. 46, 1–10.
Huo, S., Ma, C., Xi, B., Tong, Z., He, Z., Su, J., et al., 2014b. Determining ecoregional numeric nutrient criteria by stressor-response models in Yungui ecoregion lakes. China. Environ. Sci. Pollut. R. 21 (14), 8831–8846.
Huo, S., Ma, C., Xi, B., Zhang, Y., Wu, F., Liu, H., 2018. Development of methods for establishing nutrient criteria in lakes and reservoirs: a review. J. Environ. Sci. 67, 54–66.
Huo, S., Xi, B., Su, J., Zan, F., Chen, Q., Ji, D., et al., 2013. Determining reference conditions for TN, TP, SD and Chl-a in eastern plain ecoregion lakes, China. J. Environ.

Sci. 25 (5), 1001–1006.
IPCC, 2001. Climate Change 2001: The Scientific Basis. Cambridge University Press, Cambridge, UK.
Kelly, R.P., Erickson, A.L., Mease, L.A., Battista, W., Kittinger, J.N., Fujita, R., 2015. Embracing thresholds for better environmental management. Philos. T. R. Soc. B: Biol. Sci. 370 (1659), 20130276.
Lewis, W.M., Wurtsbaugh, W.A., Paerl, H.W., 2011. Rationale for Control of Anthropogenic Nitrogen and Phosphorus to Reduce Eutrophication of Inland Waters. Environ. Sci. Technol. 45 (24), 10300–10305.
Liu, L., Ma, C., Huo, S., Xi, B., He, Z., Zhang, H., et al., 2018. Impacts of climate change and land use on the development of nutrient criteria. J. Hydrol. 563, 533–542.
Marra, G., Wood, S.N., 2012. Coverage properties of confidence intervals for generalized additive model components. Scand. J. Stat. 39 (1), 53–74.
Michalak, A.M., 2016. Study role of climate change in extreme threats to water quality. Nature 535 (7612), 349–350.
Moss, R.H., Edmonds, J.A., Hibbard, K.A., Manning, M.R., Rose, S.K., Vuuren, D.P., et al., 2010. The next generation of scenarios for climate change research and assessment. Nature 463, 747–756.
Ouyang, W., Gao, X., Hao, Z., Liu, H., Shi, Y., Hao, F., 2017. Farmland shift due to climate warming and impacts on temporal-spatial distributions of water resources in a middle-high latitude agricultural watershed. J. Hydrol. 547, 156–167.
Paerl, H.W., Hall, N.S., Calandrino, E.S., 2011. Controlling harmful cyanobacterial blooms in a world experiencing anthropogenic and climatic-induced change. Sci. Total Environ. 409 (10), 1739–1745.
Paerl, H.W., Huisman, J., 2009. Climate change: a catalyst for global expansion of harmful cyanobacterial blooms. Env. Microbiol. Rep. 1, 27–37.
Paerl, H.W., Scott, J.T., McCarthy, M.J., Newell, S.E., Gardner, W.S., Havens, K.E., et al., 2016. It takes two to tango: when and where dual nutrient (N & P) reductions are needed to protect lakes and downstream ecosystems. Environ. Sci. Technol. 50 (20), 10805–10813.
PRCMEP, 2002. Water and Wastewater Monitoring and Analysis Methods. China Environmental Science Press, Beijing.
Schindler, D.W., Hecky, R.E., Findlay, D.L., Stainton, M.P., Parker, B.R., Paterson, M.J., et al., 2008. Eutrophication of lakes cannot be controlled by reducing nitrogen input: results of a 37-year whole-ecosystem experiment. Proc. Natl. Acad. Sci. U.S.A. 105 (32), 11254–11258.
Shi, K., Zhang, Y., Zhou, Y., Liu, X., Zhu, G., Qin, B., et al., 2017. Long-term MODIS observations of cyanobacterial dynamics in Lake Taihu: responses to nutrient enrichment and meteorological factors. Sci. Rep. 7, 40326.
Sienkiewicz, E., Gąsiorowski, M., Migała, K., 2017. Unusual reaction of diatom assemblage on climate changes during the last millennium: a record from Spitsbergen lake. J. Paleolimnol. 58 (1), 73–87.
Song, Y.Z., Yang, H.L., Peng, J.H., Song, Y.R., Sun, Q., Li, Y., 2015. Estimating PM2.5 concentrations in xi'an city using a generalized additive model with multi-, Monitoring Data. PloS One 10 (11), e0142149.
Taylor, K.E., 2001. Summarizing multiple aspects of model performance in a single diagram. J. Geophys. Res. 106 (D7), 7183–7192.
Tian, R., Chen, J., Sun, X., Li, D., Liu, C., Weng, H., 2018. Algae explosive growth mechanism enabling weather-like forecast of harmful algal blooms. Sci. Rep. 8 (1), 9923.
Us, E.P.A., 2006. Data Quality Assessment: Statistical Methods for Practitioners. Office of Environmental Information, Washington, DC.
Us, E.P.A., 2010. Using Stressor-Response Relationships to Derive Numeric Nutrient Criteria. Office of Water, Washington, DC.
Wang, J., Pan, F., Soininen, J., Heino, J., Shen, J., 2016. Nutrient enrichment modifies temperature-biodiversity relationships in large-scale field experiments. Nat. Commun. 7, 13960.
Wood, S.A., Borges, H., Puddick, J., Biessy, L., Atalah, J., Hawes, I., et al., 2016. Contrasting cyanobacterial communities and microcystin concentrations in summers with extreme weather events: insights into potential effects of climate change. Hydrobiologia 785 (1), 71–89.
Wood, S.N., 2017. Generalized Additive Models an introduction with. R. Chapman & Hall/CRC Press.
Wu, J., Gao, X., 2013. A gridded daily observation dataset over China region and comparison with the other datasets. Chinese J. Geophys. 56 (4), 1102–1111.
Wu, Q., Xia, X., Li, X., Mou, X., 2014. Impacts of meteorological variations on urban lake water quality: a sensitivity analysis for 12 urban lakes with different trophic states. Aquat. Sci. 76 (3), 339–351.
Wu, Z., Liu, Y., Liang, Z., Wu, S., Guo, H., 2017. Internal cycling, not external loading, decides the nutrient limitation in eutrophic lake: a dynamic model with temporal Bayesian hierarchical inference. Water Res. 116, 231–240.
Xia, X., Wu, Q., Mou, X., 2012. Advances in impacts of climate change on surface water quality. Adv. Water Sci. 23 (1), 124–133.
Xia, X., Wu, Q., Zhu, B., Zhao, P., Zhang, S., Yang, L., 2015. Analyzing the contribution of climate change to long-term variations in sediment nitrogen sources for reservoirs/lakes. Sci. Total Environ. 523, 64–73.
Xu, Y., Gao, X., Shen, Y., Xu, C., Shi, Y., Giorgi, F., 2009. A daily temperature dataset over China and its application in validating a RCM simulation. Adv. Atmos. Sci. 26 (4), 763–772.
Yan, G., Wen-Jie, D., Fu-Min, R., Zong-Ci, Z., Jian-Bin, H., 2013. surface air temperature simulations over china with CMIP5 and CMIP3. Adv. Clim. Change Res. 4 (3), 145–152.
Yang, Z., Zhang, M., Shi, X., Kong, F., Ma, R., Yu, Y., 2016. Nutrient reduction magnifies the impact of extreme weather on cyanobacterial bloom formation in large shallow Lake Taihu (China). Water Res. 103, 302–310.
Yu, L., Kong, F.X., Zhang, M., Yang, Z., Shi, X.L., Du, M.Y., 2014. The dynamics of microcystis genotypes and microcystin production and associations with environmental factors during blooms in lake chaohu, China. Toxins 6, 3238–3257.
Zhang, C., Lai, S., Gao, X., Liu, H.A., 2016a. A review of the potential impacts of climate change on water environment in lakes and reservoirs. J. Lake Sci. 28 (4), 691–700.
Zhang, Y., Zhang, L., Xu, Y., 2016b. Simulations and projections of the surface air temperature in China by CMIP5 models. Prog. Inq. Mutat. Clim. 12 (1), 10–19.
Zhang, Y.L., Wu, Z.X., Liu, M.L., He, J.B., Shi, K., Wang, M.Z., et al., 2014. Thermal structure and response to long-term climatic changes in Lake Qiandaohu, a deep subtropical reservoir in China. Limnol. Oceanogr. 59 (4), 1193–1202.